Computing Like the Brain:
The path to machine intelligence

NASA
September 17, 2013
Jeff Hawkins
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1) Discover operating principles of neocortex

2) Build systems based on these principles

Artificial Intelligence - no neuroscience

Alan Turing

"Computers are universal machines" 1935+

"Human behavior as test for machine intelligence" 1950

Major AI Initiatives

- MIT AI Lab
- 5th Generation Computing Project
- DARPA Strategic Computing Initiative
- DARPA Grand Challenge

AI Projects

- ACT-R
- Asimo
- CoJACK
- Cyc
- Deep Blue
- Global Workspace Theory
- Mycin
- SHRDLU
- Soar
- Watson

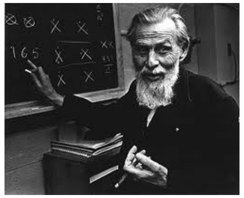
- Many more -

Pros: - Good solutions

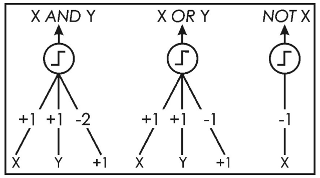
Cons: - Task specific
- Limited or no learning

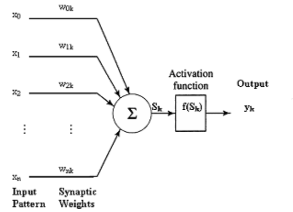
Artificial Neural Networks – minimal neuroscience

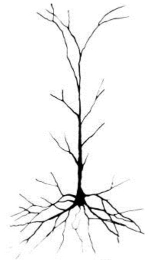
Warren McCulloch
Walter Pitts

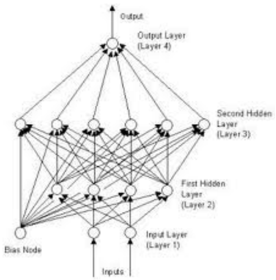


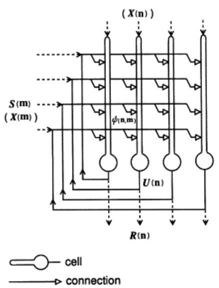
"Neurons as logic gates" 1943
Proposed first artificial neural network











ANN techniques

- Back propagation
- Boltzman machines
- Hopfield networks
- Kohonen networks
- Parallel Distributed Processing

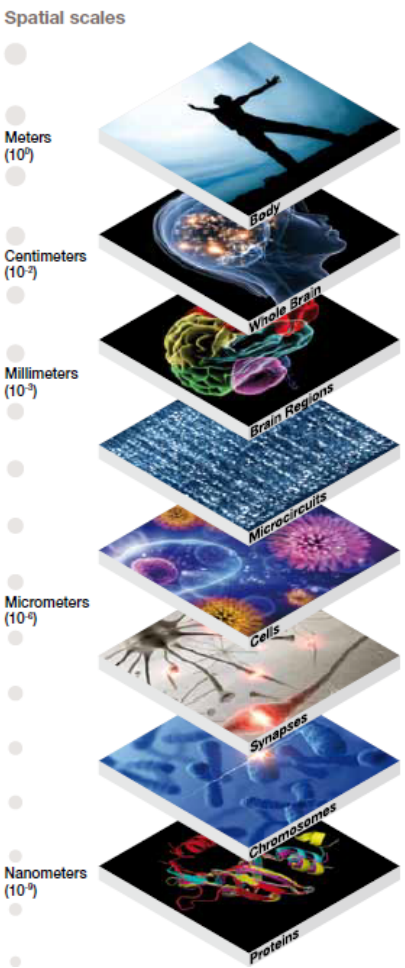
- Machine learning
- Deep Learning

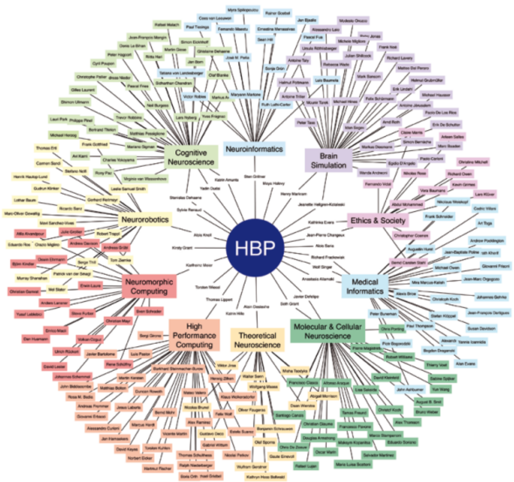
Pros: - Good classifiers
- Learning systems

Cons: - Limited capabilities
- Not brain like

Whole Brain Simulator – maximal neuroscience

The Human Brain Project





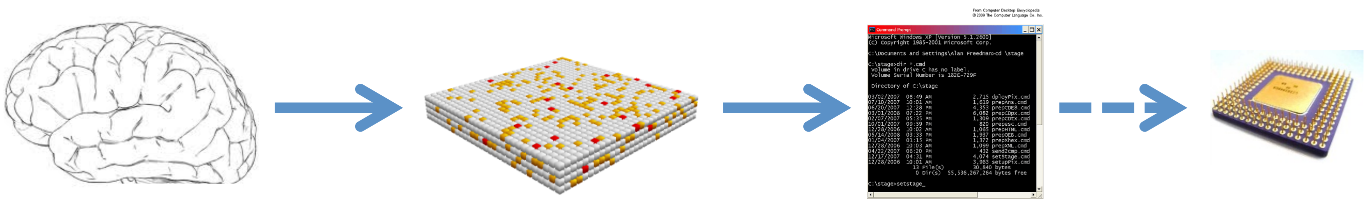
Blue Brain simulation

No theory

No attempt at Machine Intelligence

1) Discover operating principles of neocortex

2) Build systems based on these principles



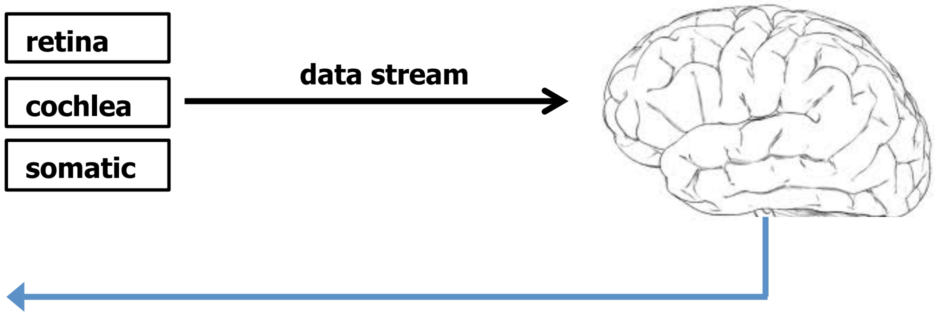
Anatomy, Physiology

Theoretical principles

Software

Silicon

The neocortex is a memory system.

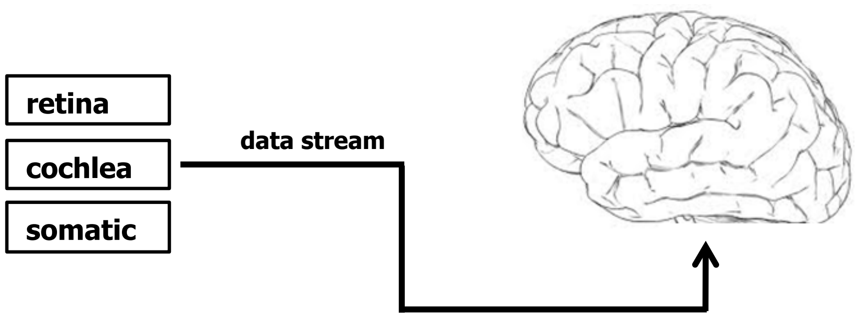


The neocortex learns a model from sensory data

- predictions
- anomalies
- actions

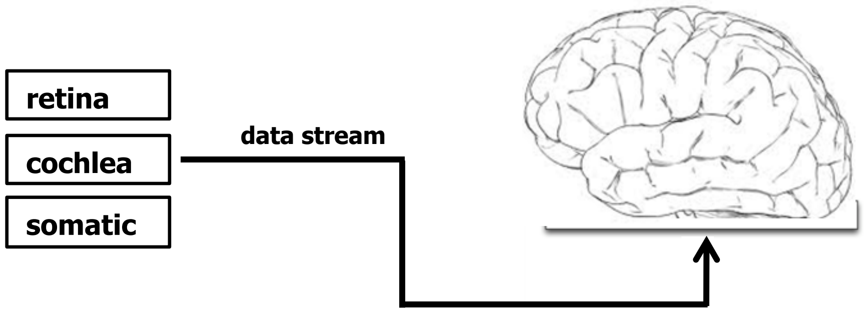
The neocortex learns a <u>sensory-motor model</u> of the world

Principles of Neocortical Function



1) On-line learning from streaming data

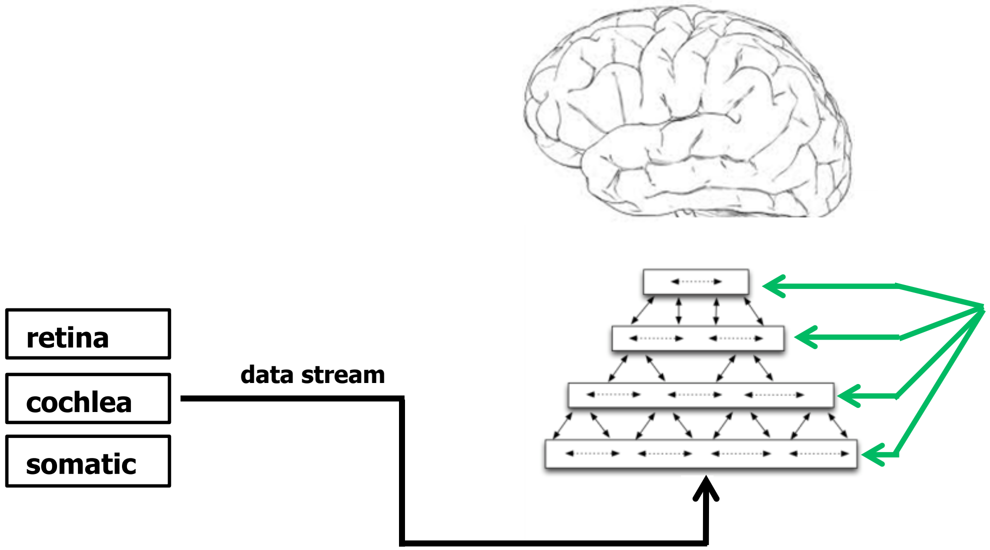
Principles of Neocortical Function



1) On-line learning from streaming data

2) Hierarchy of memory regions

Principles of Neocortical Function

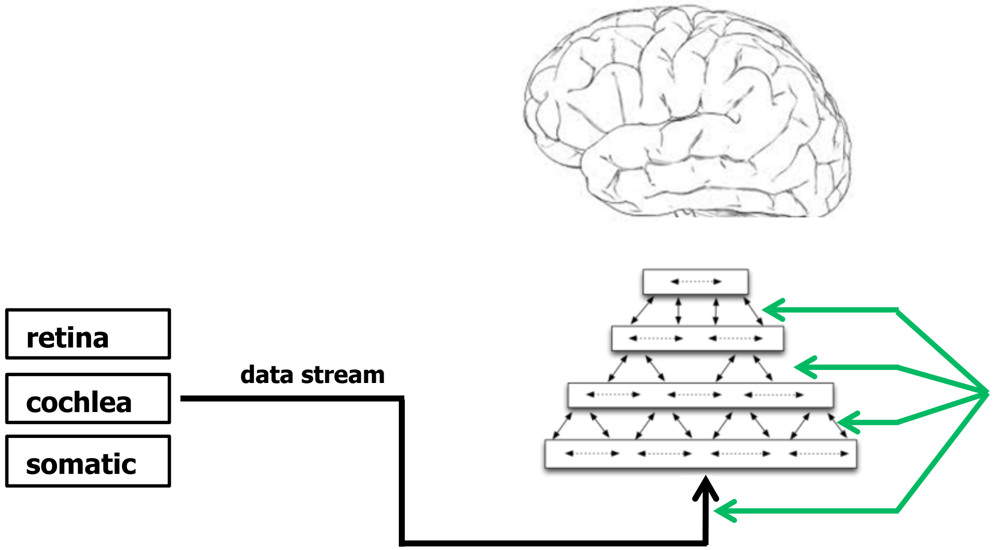


1) On-line learning from streaming data

2) Hierarchy of memory regions

3) Sequence memory
   - inference
   - motor

Principles of Neocortical Function



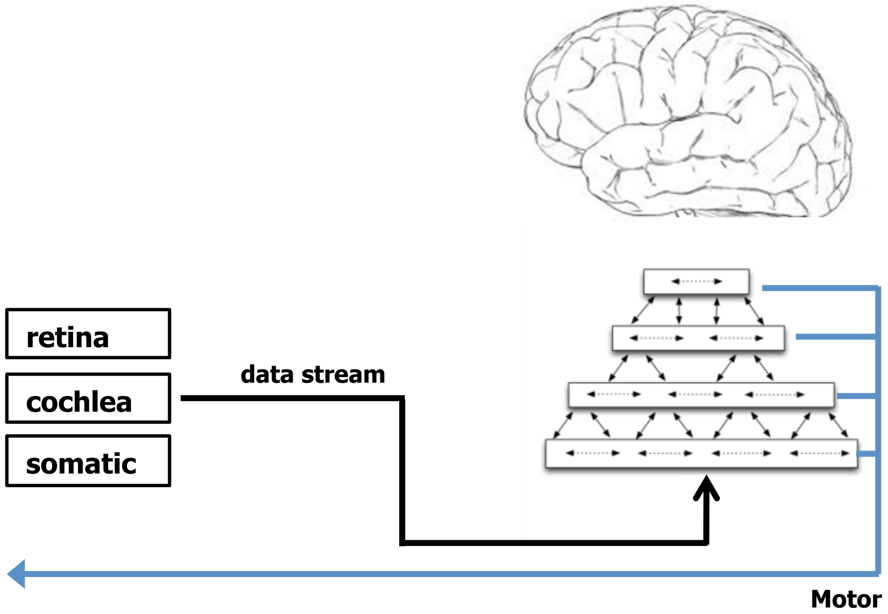
1) On-line learning from streaming data

2) Hierarchy of memory regions

3) Sequence memory

4) Sparse Distributed Representations

Principles of Neocortical Function



1) On-line learning from streaming data

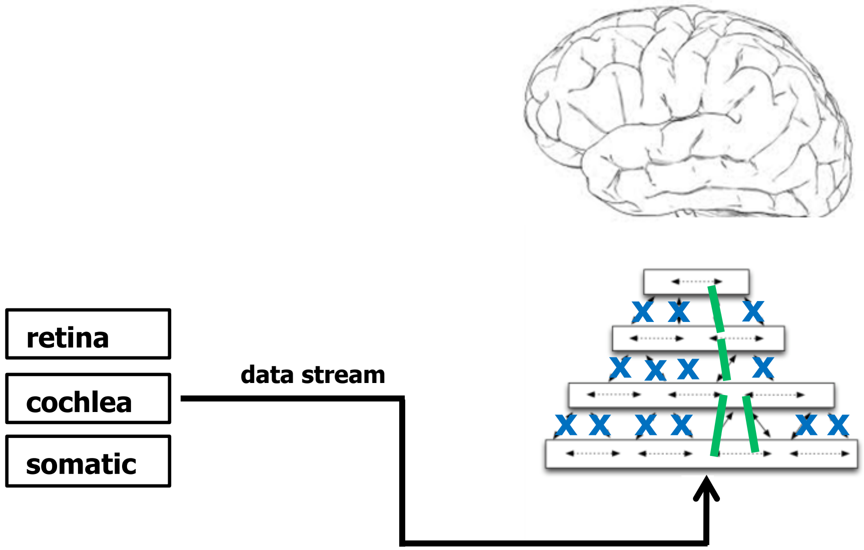
2) Hierarchy of memory regions

3) Sequence memory

4) Sparse Distributed Representations

5) All regions are sensory and motor

Principles of Neocortical Function



1) On-line learning from streaming data

2) Hierarchy of memory regions

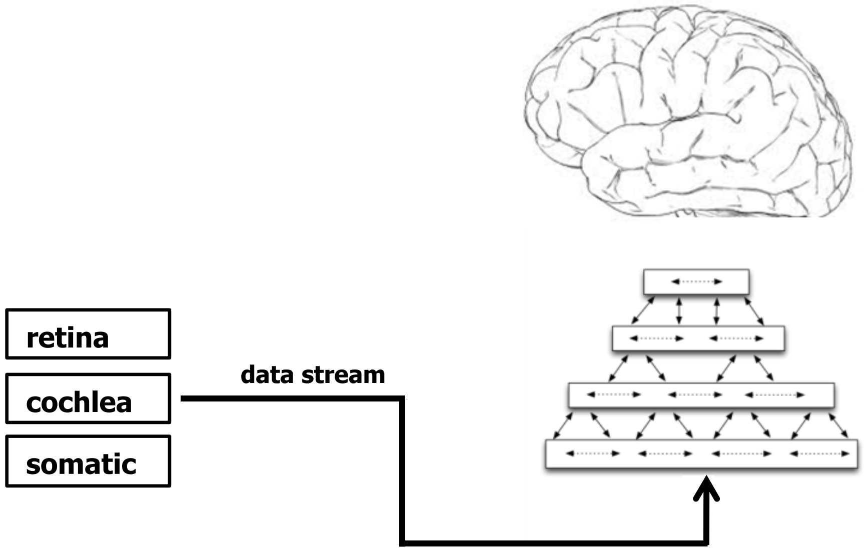
3) Sequence memory

4) Sparse Distributed Representations

5) All regions are sensory and motor

6) Attention

Principles of Neocortical Function



1) On-line learning from streaming data

2) Hierarchy of memory regions

3) Sequence memory

4) Sparse Distributed Representations

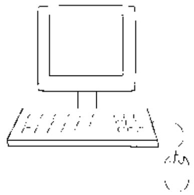
5) All regions are sensory and motor

6) Attention

These six principles are necessary and sufficient for biological and machine intelligence.

- All mammals from mouse to human have them
- We can build machines like this

Dense Representations

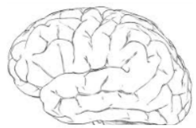


- Few bits (8 to 128)
- All combinations of 1's and 0's
- Example: 8 bit ASCII

  01101101   = m

- Individual bits have no inherent meaning
- Representation is assigned by programmer

Sparse Distributed Representations (SDRs)



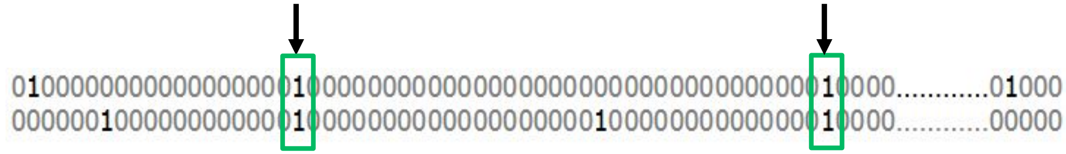
- Many bits (thousands)
- Few 1's mostly 0's
- Example: 2,000 bits, 2% active

  01000000000000000001000000000000000000000000000000000000000010000…………01000

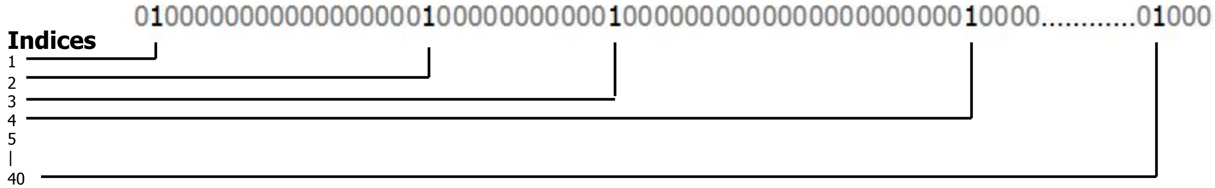
- Each bit has semantic meaning
- Meaning of each bit is learned, not assigned

SDR Properties

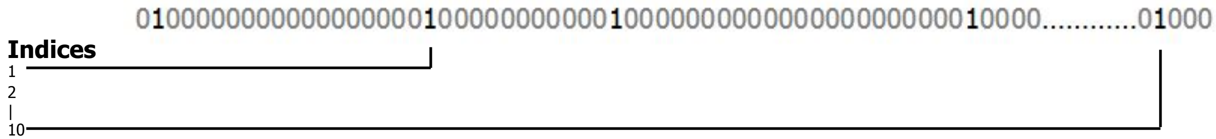
1) **Similarity**:
shared bits = semantic similarity



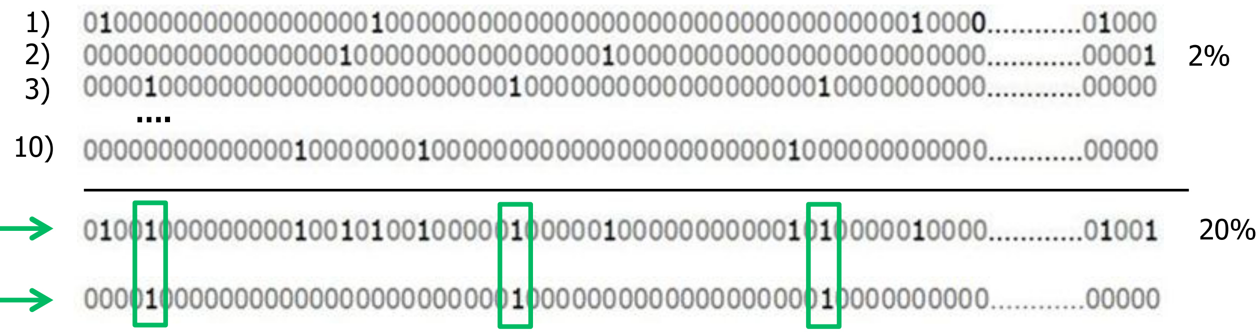
2) **Store and Compare**:
store indices of active bits



subsampling is OK



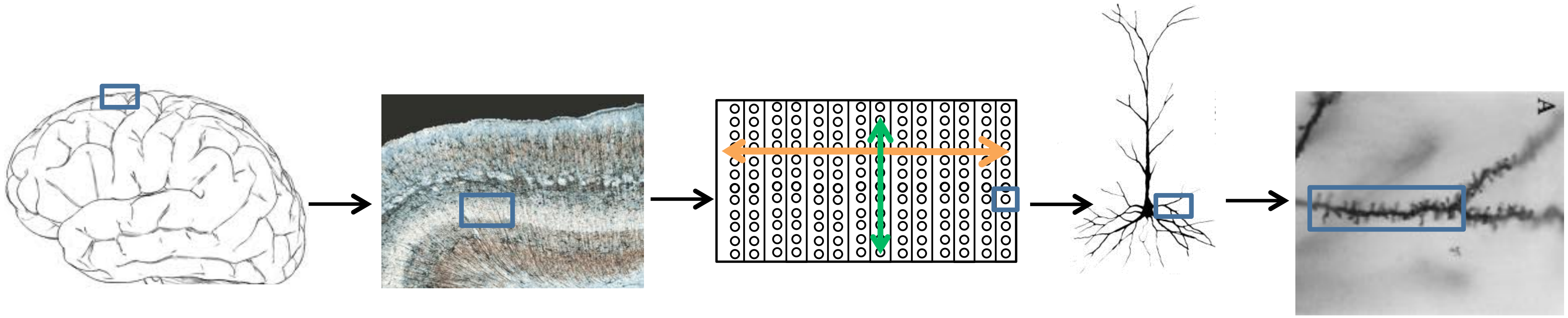
3) **Union membership**:

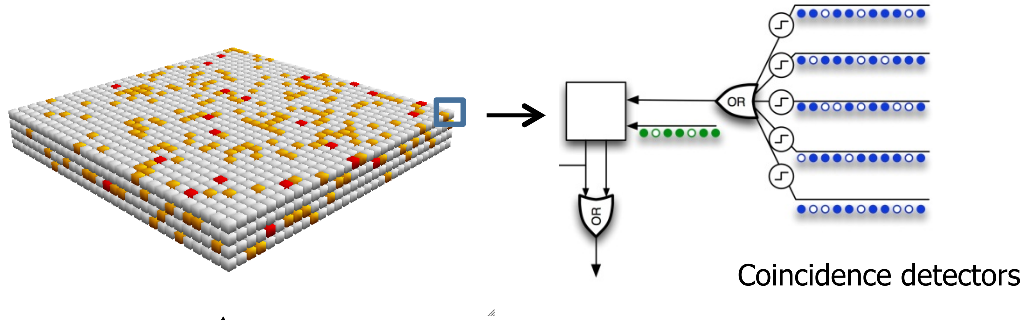


Union

Is this SDR
a member?

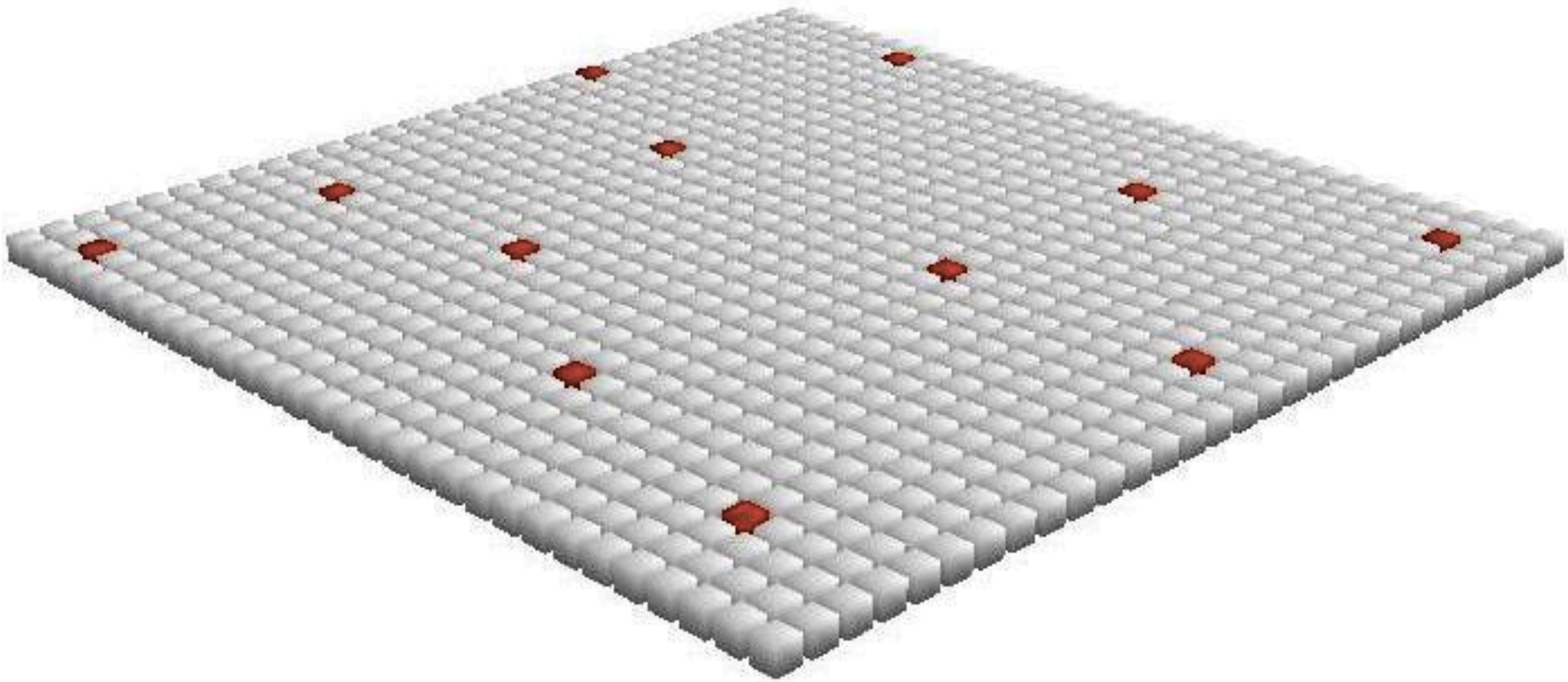
Sequence Memory (for inference and motor)





How does a layer of neurons learn sequences?

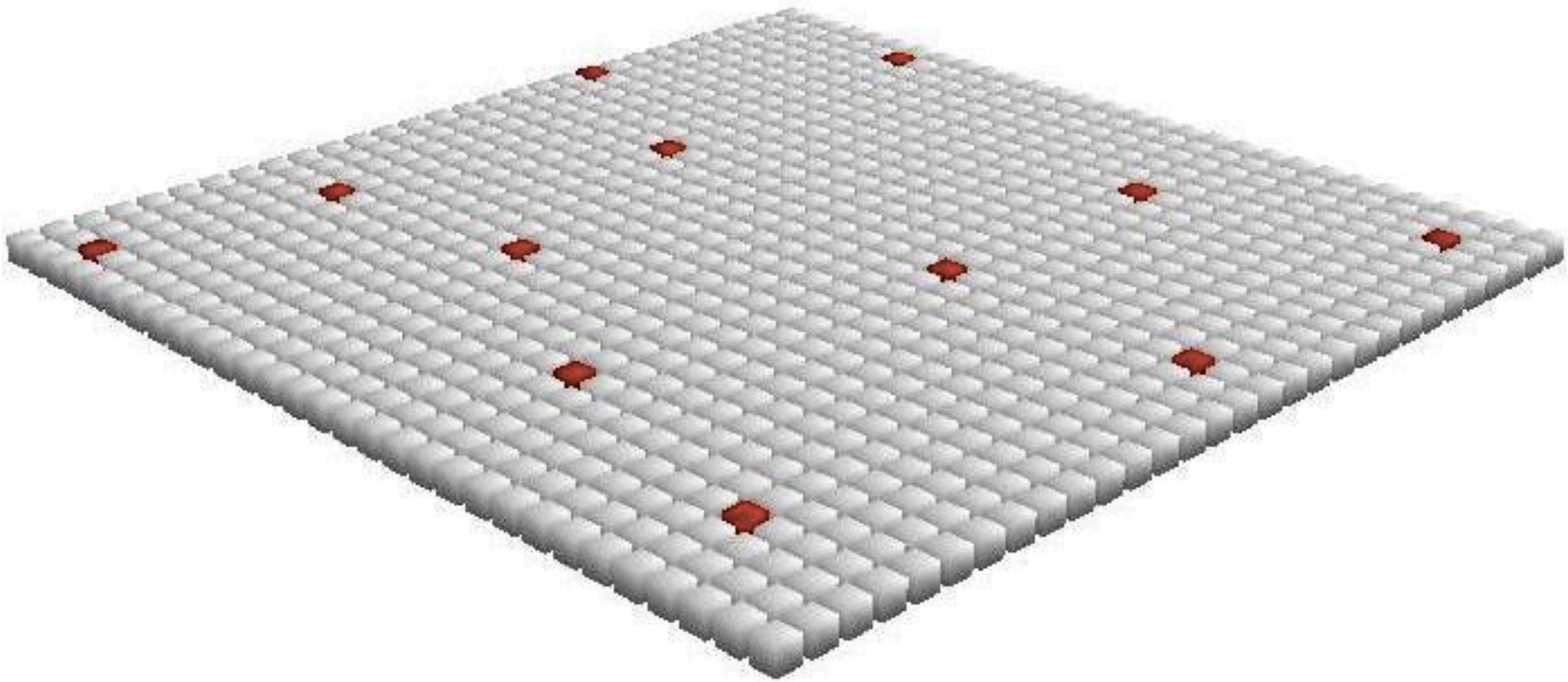
Each cell is one bit in our Sparse Distributed Representation



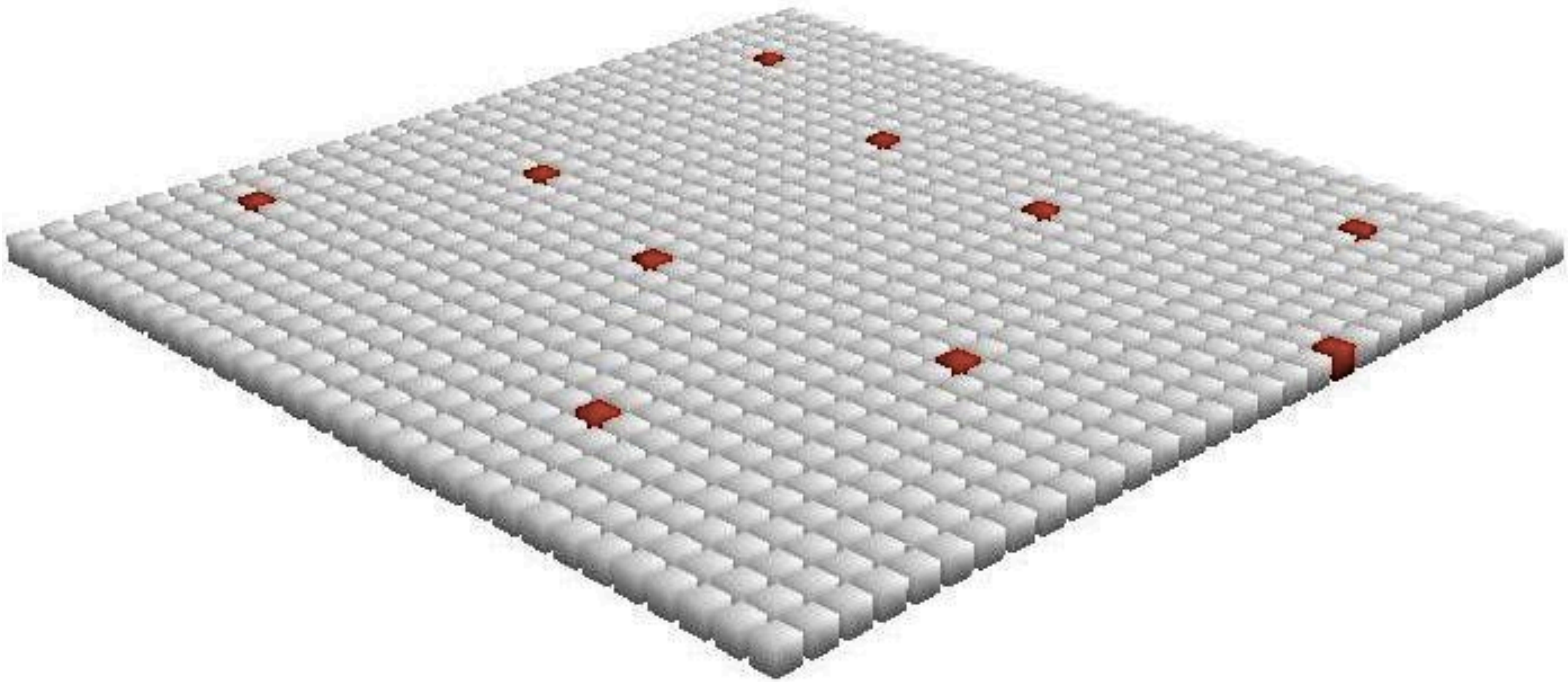
SDRs are formed via a local competition between cells.

All processes are local across large sheets of cells.

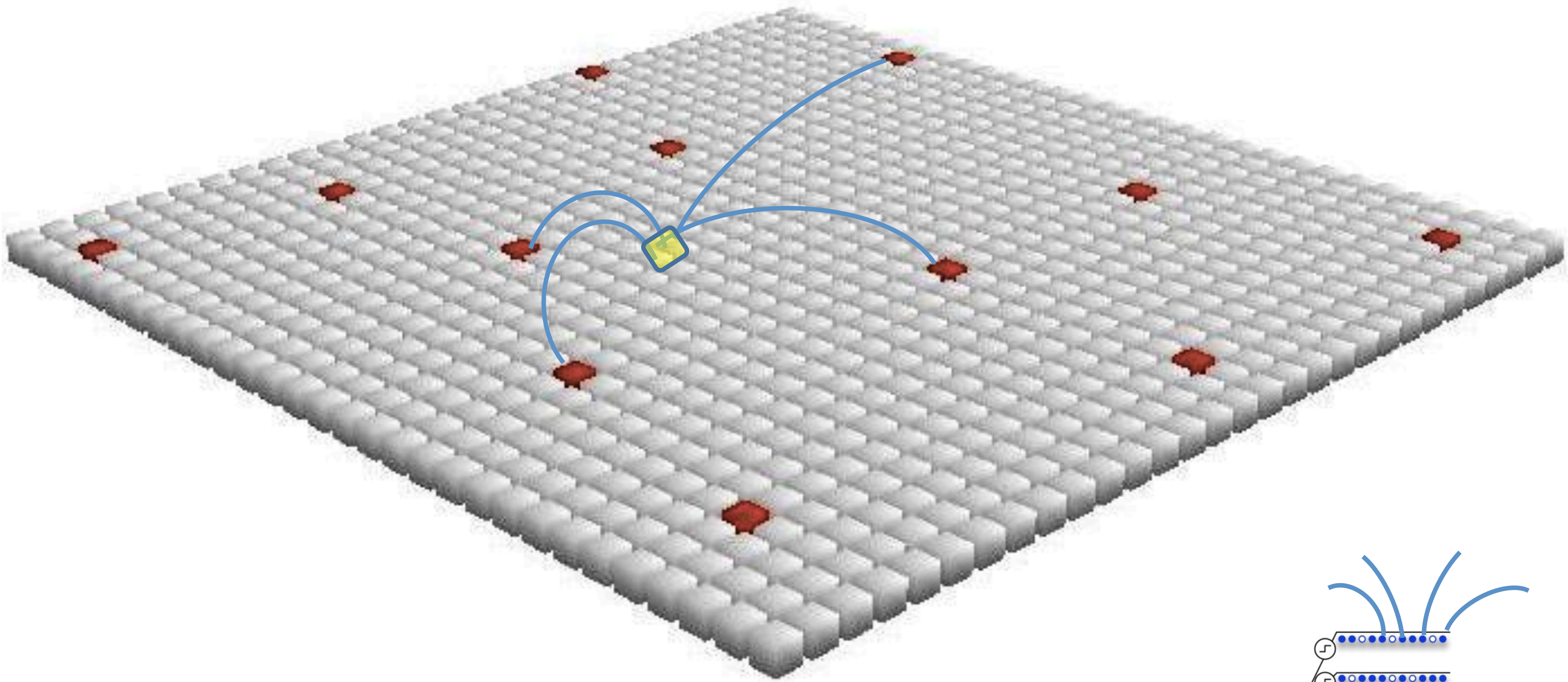
SDR (time =1)

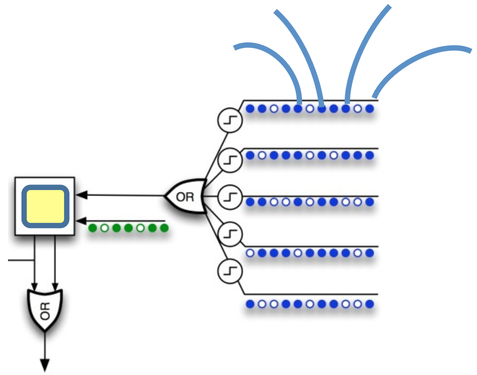


SDR (time =2)

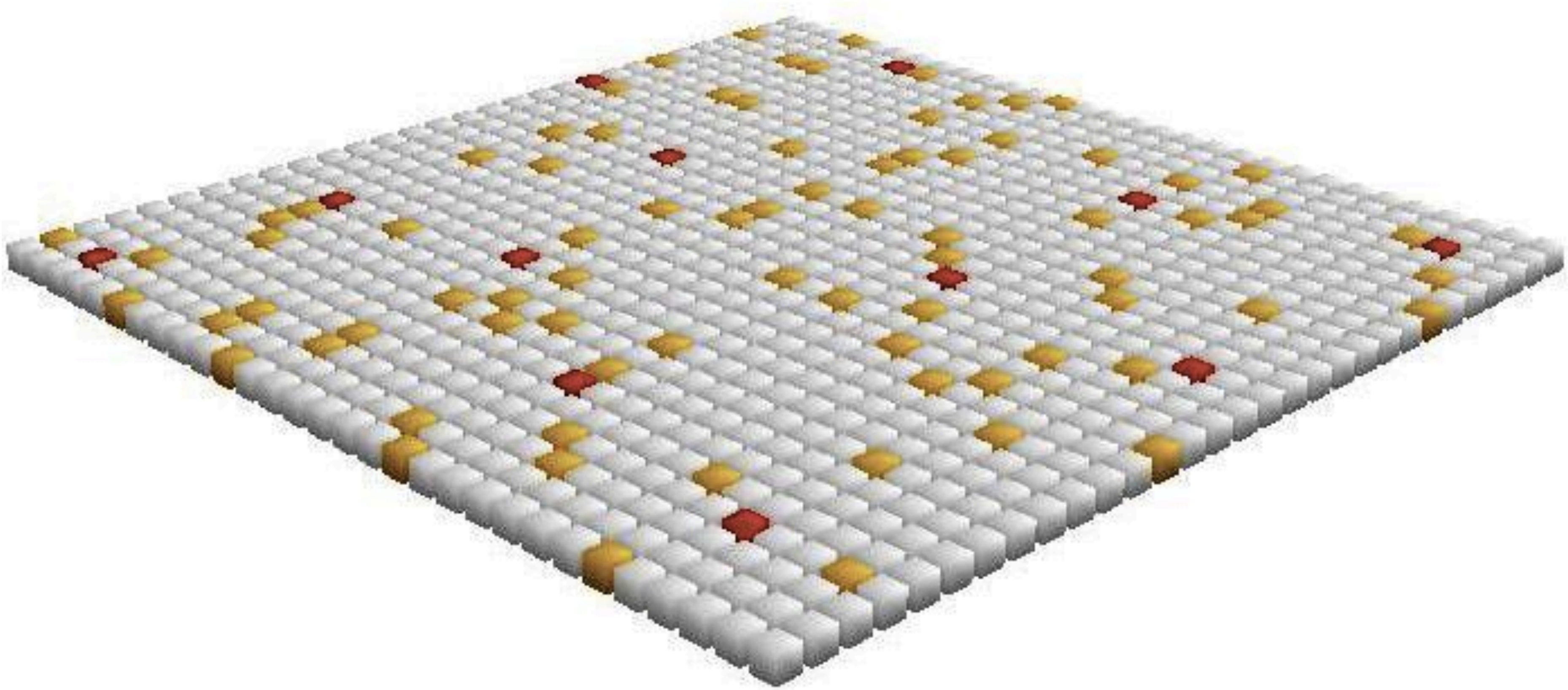


Cells form connections to subsample of previously active cells.
Predicts its own future activity.



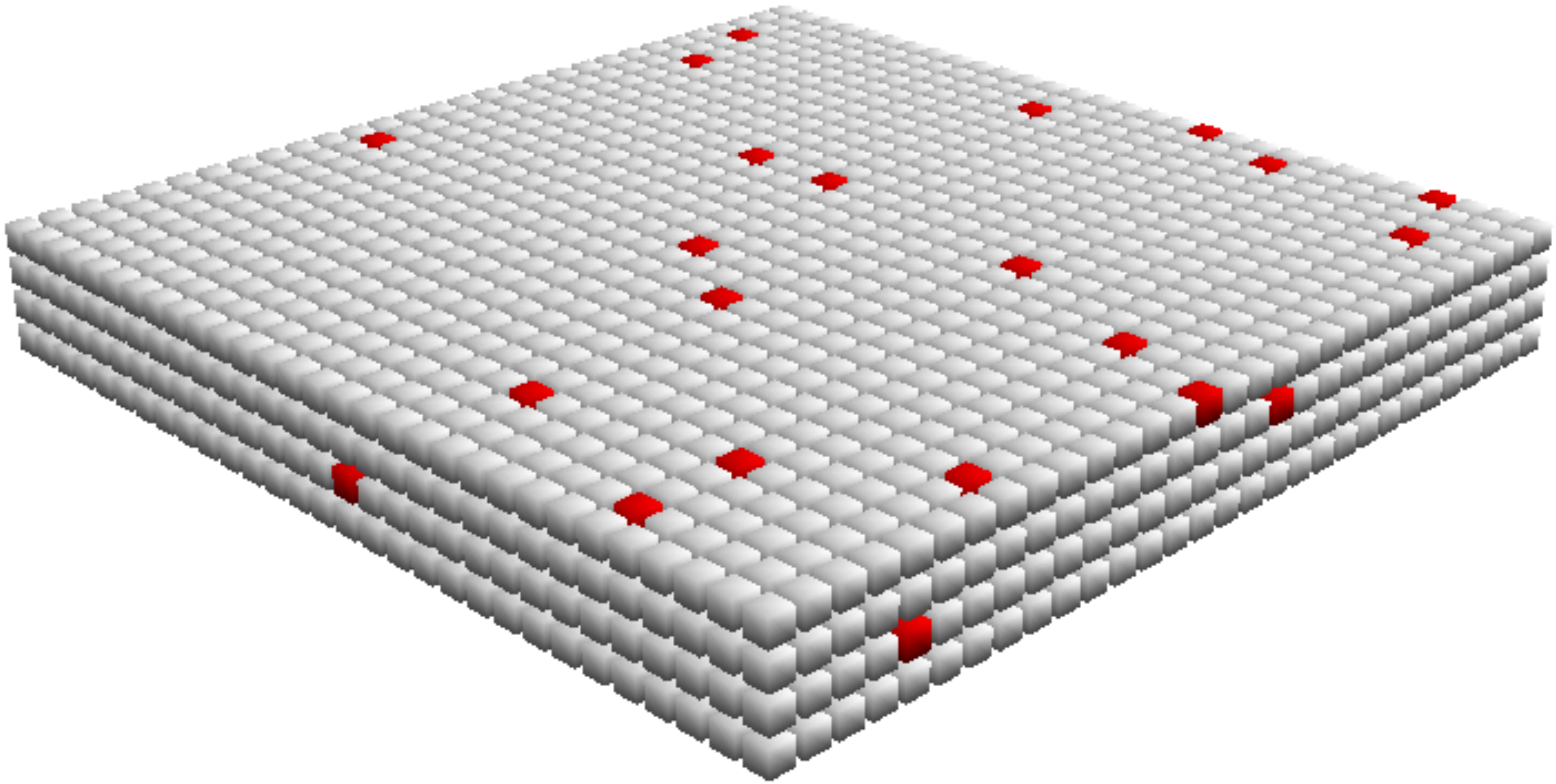


Multiple Predictions Can Occur at Once

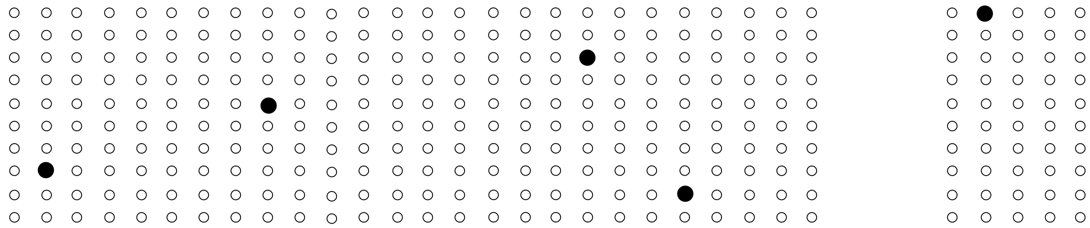


With one cell per column, 1st order memory
We need a high order memory

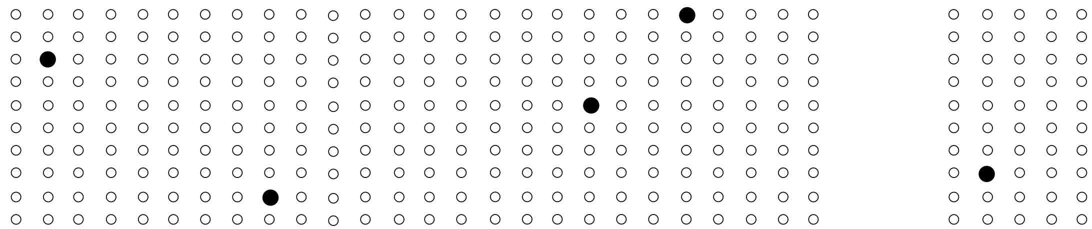
High order sequences are enabled with multiple cells per column.



High Order Sequence Memory



0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0............0 1 0 0 0



0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0............0 1 0 0 0

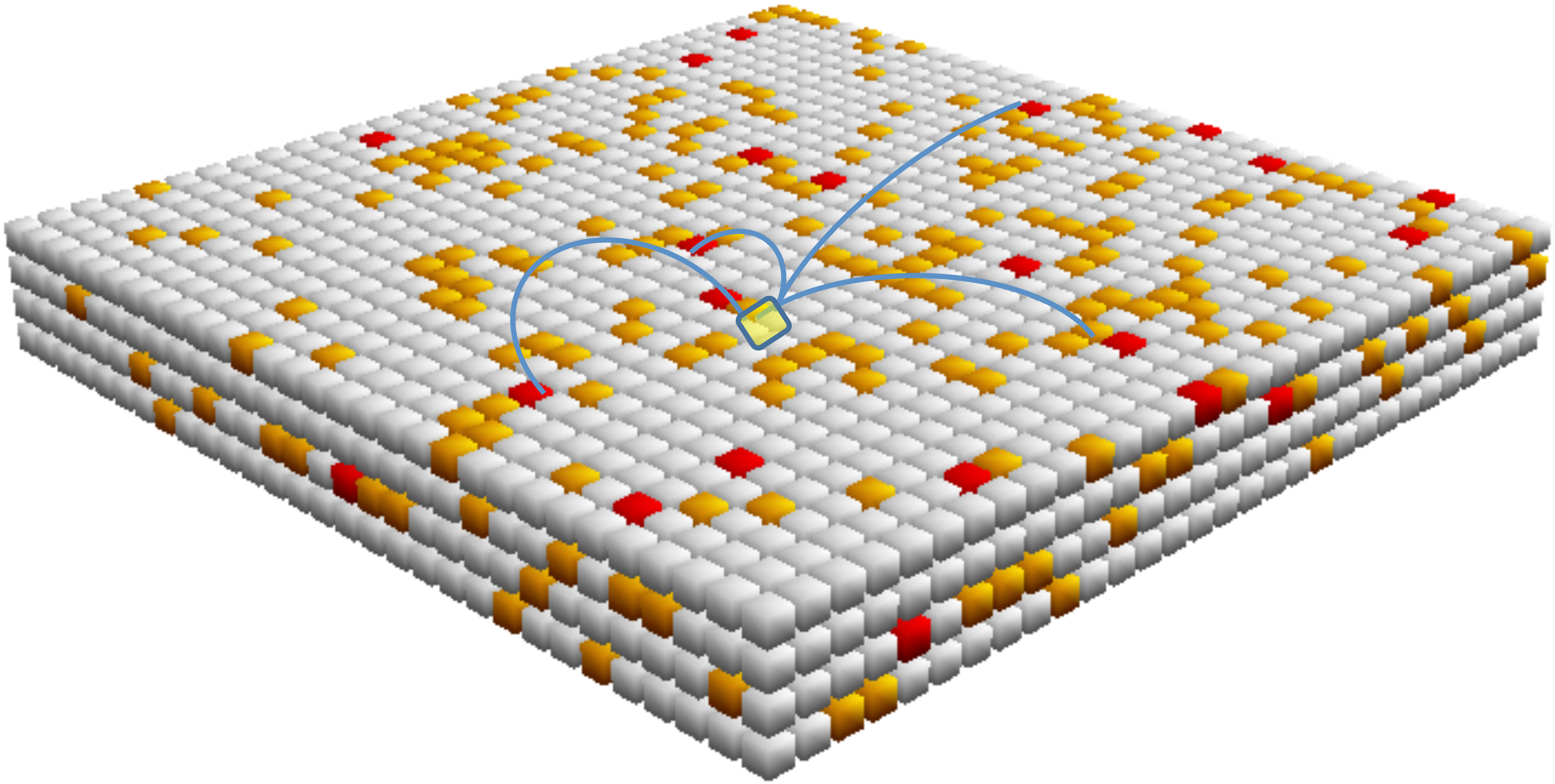
40 active columns, 10 cells per column

= 10^{40} ways to represent the same input in different contexts

A-B-C-D-E

X-B'-C'-D'-Y

High Order Sequence Memory



Distributed sequence memory

Works across large areas
High order, high capacity
Multiple simultaneous predictions
Semantic generalization

Online learning

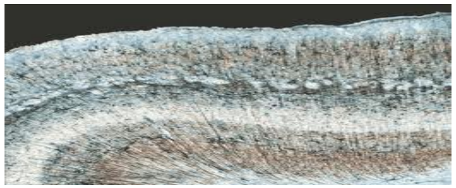
- Learn continuously, no batch processing
- If pattern repeats, reinforce, otherwise forget it

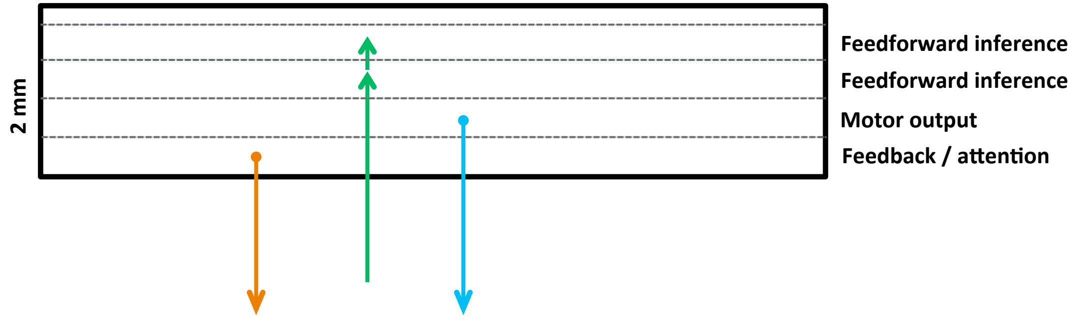
Learning is the growth of new synapses.

Connection strength is binary
Connection permanence is a scalar
Training changes permanence

Cortical Region

2 mm





Cortical Region

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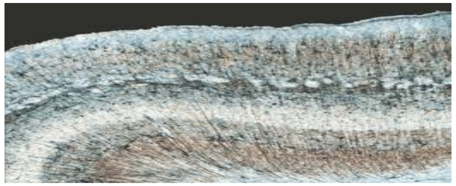
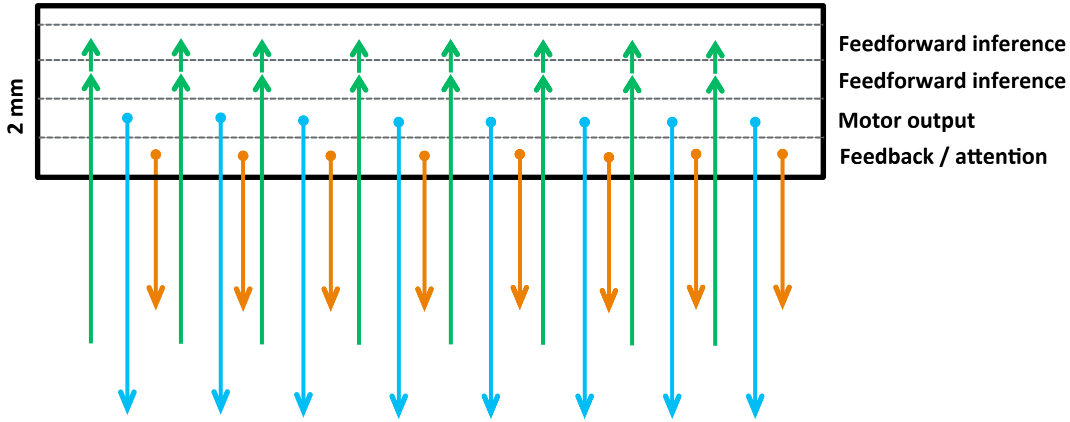
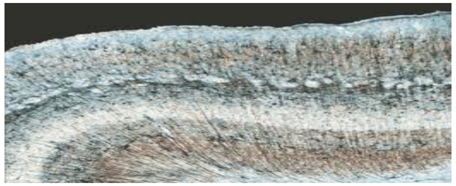
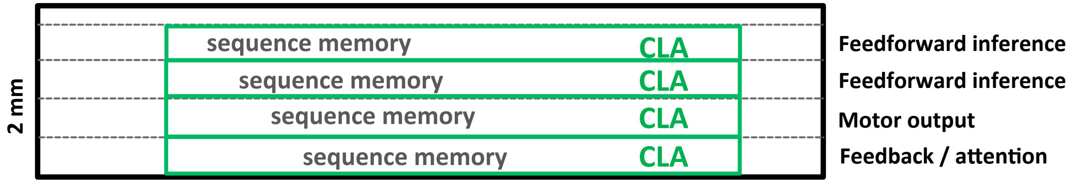




Cortical Region

2 mm





Evidence suggests each layer is implementing a CLA variant

Three Current Directions

1) Open Source Project

- NuPIC: CLA open source software and community
- Improve algorithms, develop applications

2) Commercialization

- GROK: Predictive analytics using CLA
- Commercial value generates investment $

3) Custom CLA Hardware

- Needed for scaling research and commercial applications
- IBM, Seagate, Sandia Labs, DARPA

NuPIC: CLA Open Source Project

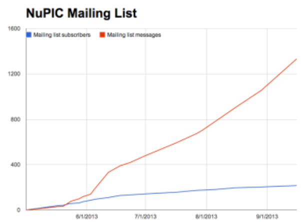
www.Numenta.org

Single source tree (used by GROK)

GPLv3 license

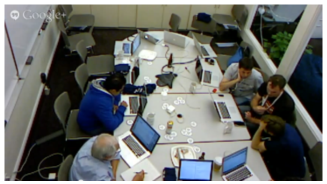
Active community

- 215 mail list subscribers
- 20 messages per day
- growing
- full time manager, Matt Taylor

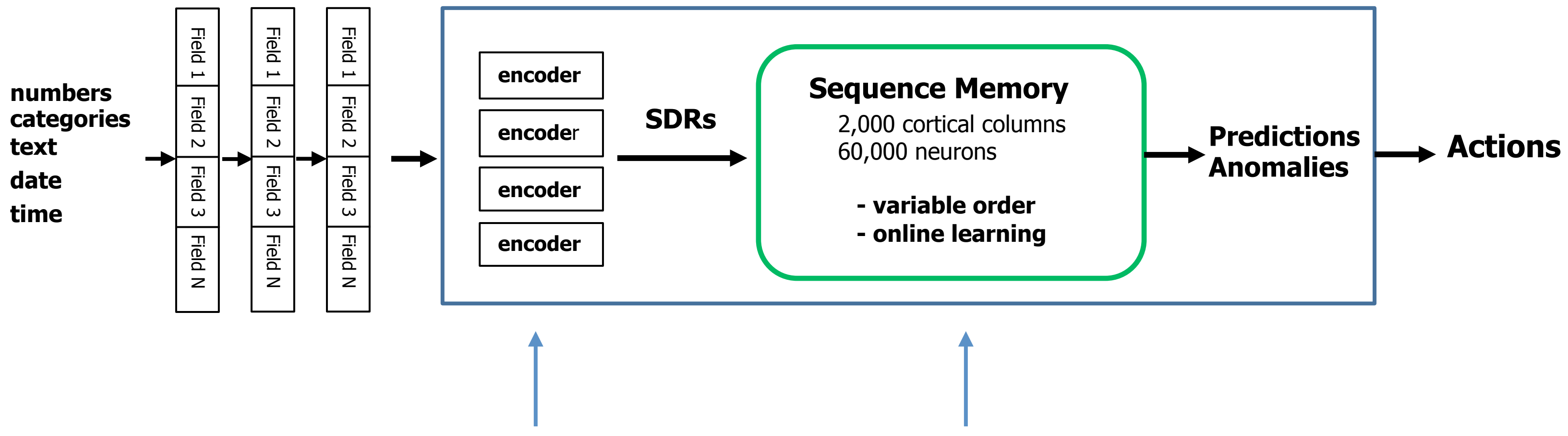


Next hackathon November 2 & 3 in San Francisco

- NLP using SDRs
- Sensory-motor integration using CLA discussion



GROK: Predictive Analytics Using CLA



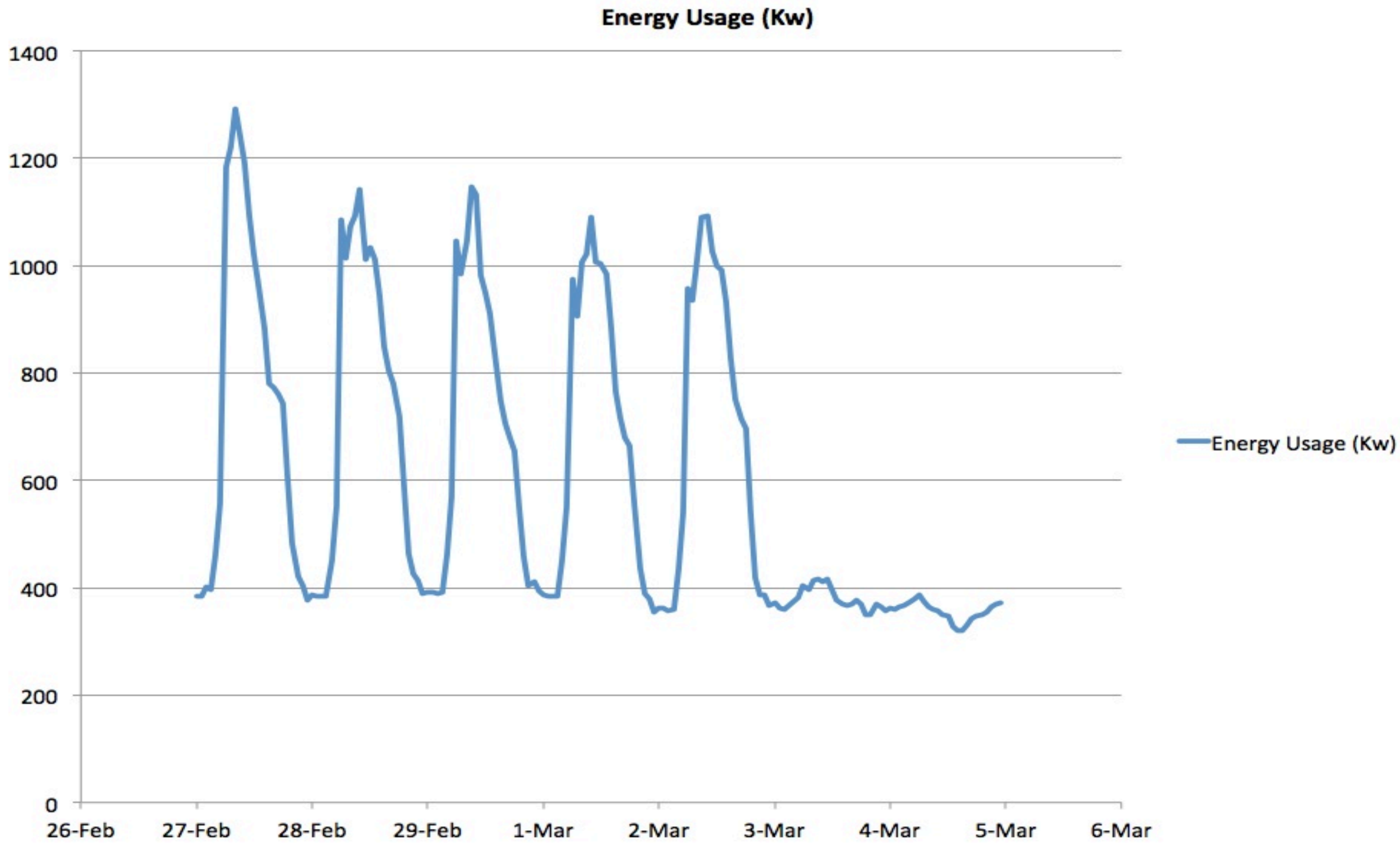
Encoders

Convert native data type to SDRs

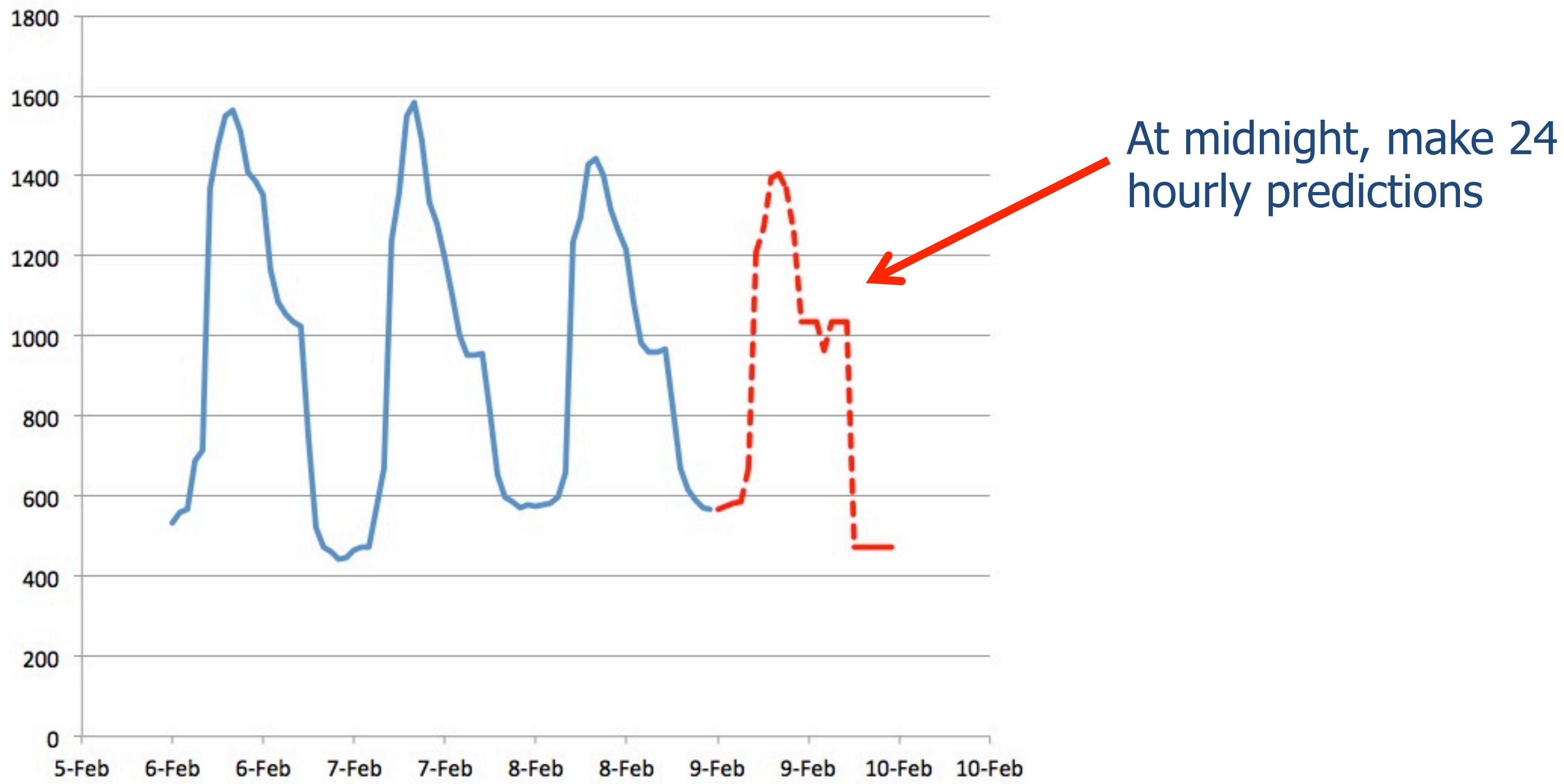
CLA

Learns spatial/temporal patterns
Outputs
- predictions
  anomalies

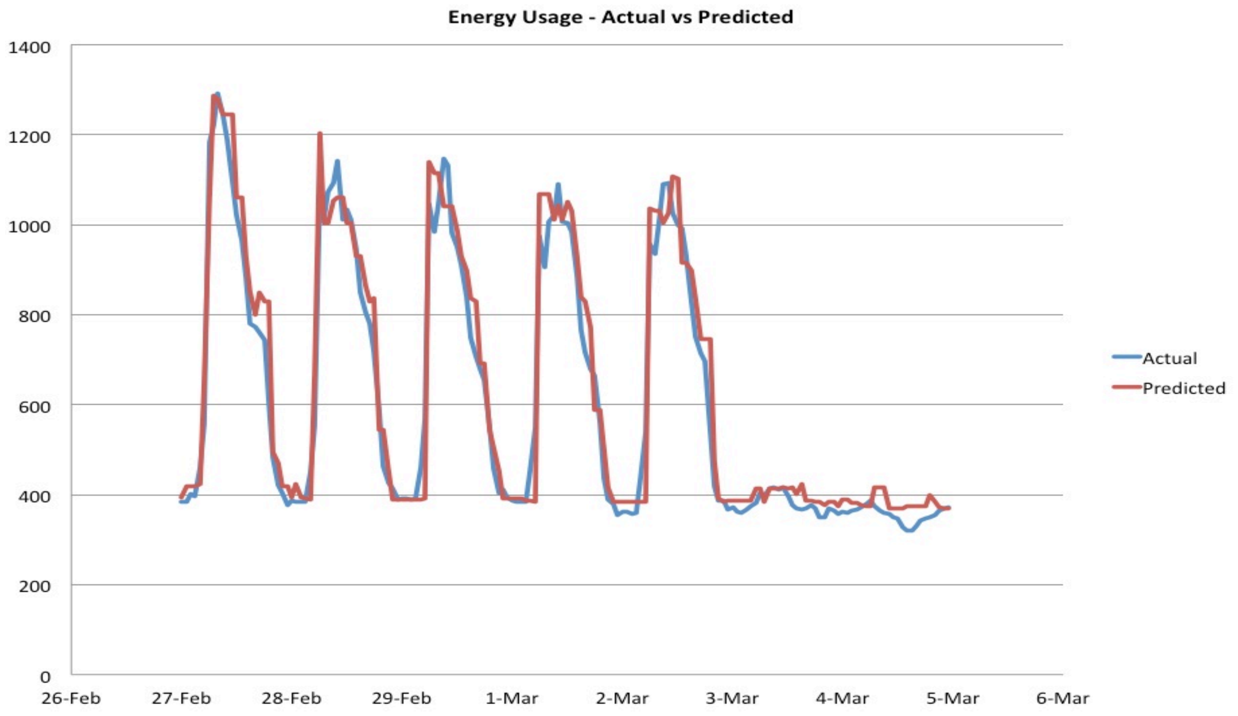
GROK example: Factory Energy Usage



Customer need



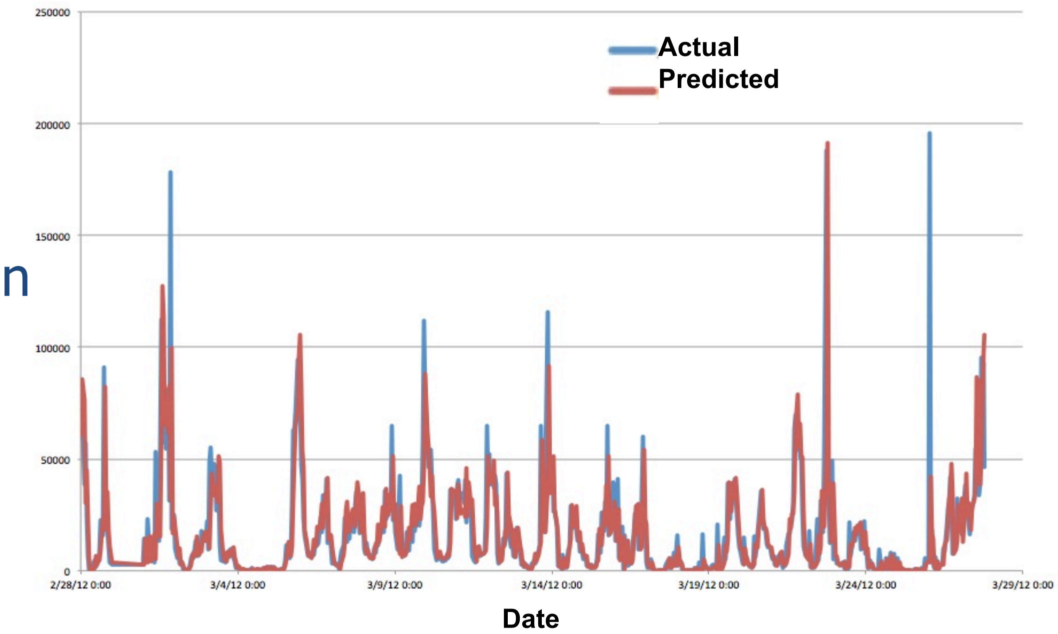
GROK Predictions and Actuals



GROK example: Predicting Server Demand

Grok used to predict server demand

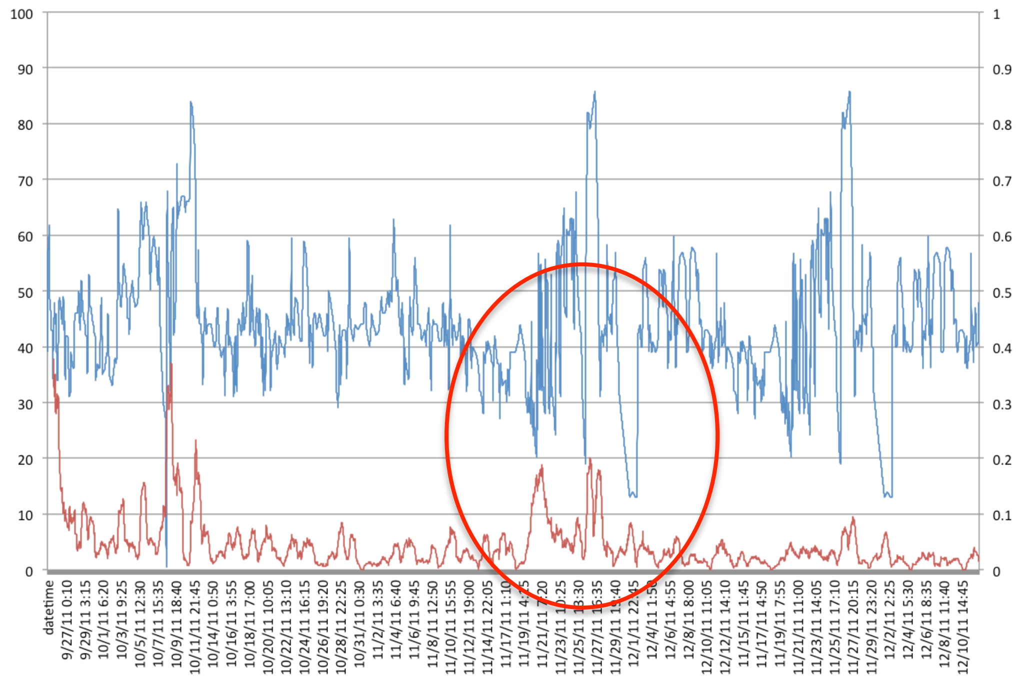
Approximately 15% reduction in AWS cost



Server demand, Actual vs. Predicted

GROK example: Detecting Anomalous Behavior

Grok builds model of data, detects changes in predictability.



Gear bearing temperature & Grok Anomaly Score

GROK going to market for anomaly detection in I.T. 2014

Custom CLA Hardware

IBM

- Almaden Labs
- Joint research agreement
- Winfried Wilcke

DARPA

- “Cortical Processor”
- “HTM” (Hierarchical Temporal Memory)
- CLA is prototype primitive
- Dan Hammerstrom

Seagate

Sandia Labs

Future of Machine Intelligence

Future of Machine Intelligence

Definite

- Faster, Bigger
- Super senses
- Fluid robotics
- Distributed hierarchy

Maybe

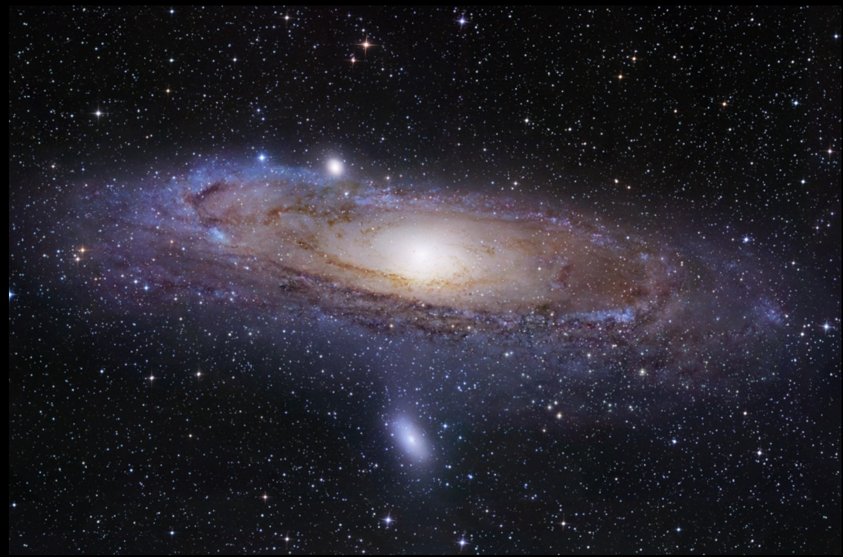
- Humanoid robots
- Computer/Brain interfaces for all

Not

- Uploaded brains
- Evil robots
- Friendly uses only

Why Machine Intelligence?

Live better



Learn more

Thank You